# Continuing to Explore New Frontiers: Research to Integrate Administrative Data into the American Community Survey

ACS Webinar May 13, 2020

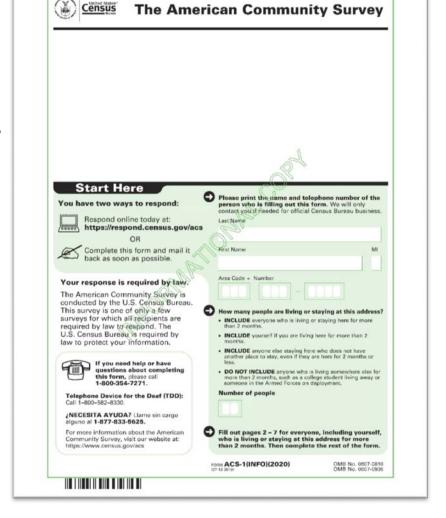


This presentation is released to inform interested parties of ongoing research and to encourage discussion of work in progress. Any views expressed on statistical, methodological, operational, or technical issues are those of the presenters and not necessarily those of the U.S. Census Bureau.

# **American Community Survey**

The American Community Survey is on the leading edge of survey design, continuous improvement, and data quality

- The nation's **most current, reliable, and accessible data** source for local statistics on critical planning topics such as age, children, veterans, commuting, education, income, and employment
- Surveys 3.5 million addresses and informs over \$675 billion of Federal government spending each year
- Covers **40+ topics**, supports over **300** evidence-based Federal government uses, and produces **11 billion** estimates each year
- Three key annual data releases:
  - 1-year Estimates (for large populations)
  - 1-year Supplemental Estimates (for small populations)
  - 5-year Estimates (for very small populations)





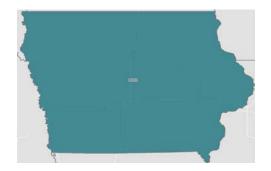
# **ACS Content Overview**

POPULATION		HOUSING	
SOCIAL Ancestry Citizenship Disability Educational Attainment Fertility Grandparents Language Marital Status Migration School Enrollment Veterans	DEMOGRAPHIC Age Hispanic Origin Race Relationship Sex ECONOMIC Class of Worker Commuting Employment Status Food Stamps (SNAP) Health Insurance Hours/Week, Weeks/Year Income Industry & Occupation	Computer & Internet Use Costs (Mortgage, Rent, Taxes, Insurance) Heating Fuel Home Value Occupancy Plumbing/Kitchen Facilities Structure Tenure (Own/Rent) Utilities Vehicles Year Built/ Year Moved In	



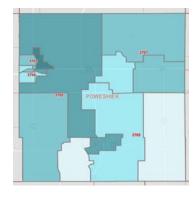
# **ACS Geographic Concepts**

### **STATE**



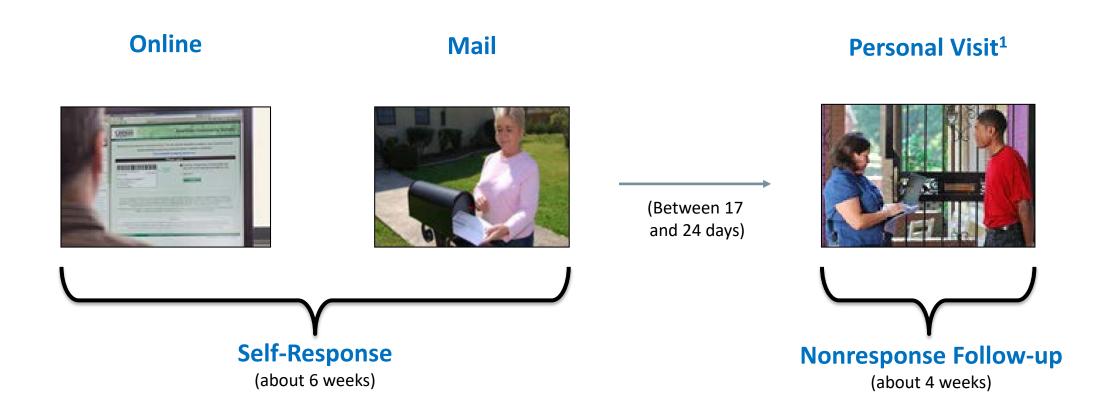
# CENSUS TRACT CENSUS TRACT POMESHAR POMESHAR

### **BLOCK GROUP**





# **ACS Data Collection Process**





# Why and How to Use Administrative Data?



Increase data quality by filling in missing responses and using administrative data to evaluate and enrich survey data



Save time and improve respondent experience by reducing the number of questions asked on the ACS



Provide cost savings by identifying vacant housing units and reducing the need for follow-up visits



Mandated by Title 13 of the U.S. Code to use already available information



Identify Data
Sources



Evaluate Sources with Guiding Principles



Identify Best Candidates





**Experiment** 



# Identify Data Sources



Evaluate Sources with Guiding Principles



Identify Best
Candidates
(Replacement, Allocation, Etc.)



**Experiment** 

### **Federal Data**

(e.g., Internal Revenue Service, Social Security Administration)

### **State and Local Data**

(e.g., Temporary Assistance for Needy Families, Supplemental Nutrition Assistance Program)

### **Third-Party Data**

(e.g., Black Knight property and tax foreclosure, VSGI consumer households)



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Authorization

Availability

Conceptual Alignment

Coverage

**Data Source** 

Disclosure Avoidance

Impacts on Estimates

Intended Use

Population Universe

Quality

Reliability

Temporal Alignment



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### **Most Promising:**

Property Value Real Estate Tax Year Built

Acreage

### **Less Promising:**

Part of a Condominium

Phone Service

Facilities (Kitchen/Bathroom)

Fuel Type

Tenure

Have a Mortgage

First/Secondary Mortgage

**Payment** 

Number of (Bed)Rooms

Agricultural Sales



# Identify Data Sources



# Evaluate Sources with Guiding Principles



# Identify Best Candidates

(Replacement, Allocation, Etc.)



### **Experiment**

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**Predicting Vacant Housing** 

**Units** to reduce need for followup visits

Replace survey responses with administrative data to reduce the number of questions asked of respondents

**Fill in missing values** to improve data quality

Enrich ACS data through linkages to administrative data to expand topics covered

Use administrative records to improve measurement of income



# **Today's Presentations**

**Predicting Vacant Housing Units in the ACS** 

Andrew Keller | Andrew.D.Keller@census.gov

Analyzing Differences between Survey Responses and Administrative Data for Property Value

R. Chase Sawyer | Robert.C.Sawyer@census.gov

Using Alternative Data Sources to Fill-in Missing Values for Demographic Characteristics in the ACS

Sandra L. Clark | Sandra.L.Clark@census.gov

Linking ACS and IRS Data to Assess College Attendance and Completion by Family Income

Leah Clark | Leah.R.Clark@census.gov



# Predicting Vacant Housing Units in the American Community Survey

Andrew Keller
Decennial Statistical Studies Division



# Outline

Background

Research Objective and Methods

Simulation

Discussion



# Background

- 2020 Census
  - Can we use administrative records (AR) to inform Nonresponse Followup (NRFU) operation?
  - Use AR to model occupied, vacant, delete statuses of NRFU universe
  - Modify contact strategy where we have high confidence in address status
  - Conduct one visit to units with high confidence of final status via models
- Apply same concept to predict units with high confidence of vacancy in American Community Survey (ACS)
  - Conceptual Difference: 2020 Census determination is point-in-time
- Use probability to inform contact or sampling strategy



# Model

- Logistic Model: Dependent Variable is vacancy outcome status
- Use Previous Year(s) of ACS to form training data
  - Administrative Records data of the same vintage
  - Operational Data
  - Address-Level information from Master Address File
  - Block Group-level information from ACS Planning Database
- Apply parameter estimates to current vintage of ACS data
- Predicted probability of vacancy for every ACS unit in mailable Computer Assisted Personal Interview (CAPI) universe



- Administrative Records data
  - Aggregated public information purchased by Census Bureau consisting of local tax, deed, and mortgage information
  - Using information concerning land use, absence of owner at address, ownership rights on the unit
  - Third-Party AR data providing information about persons at addresses
  - National Change of Address information from United States Postal Service (USPS)



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### Operational Data

- Mailing operations (undeliverable as addressed from USPS)
- Indication of vacancy from internet response



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- Mailing operations (undeliverable as addressed from USPS)
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  - Delivery Sequence File status (Residential, Commercial, Excluded from Delivery Statistics)
  - Housing Unit Type (Multi, Single, Trailer, Other)
  - Delivery Point Type

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- Block Group-level information from ACS Planning Database
  - Poverty, Rental, Other Language rates, Hispanic



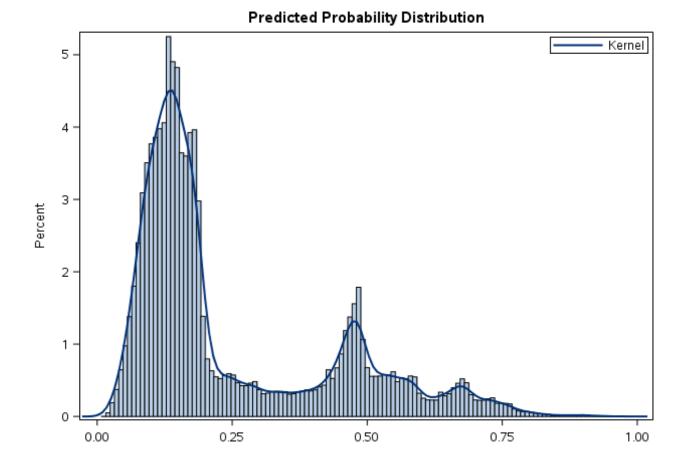
# Simulation Setup

- Take mailable CAPI universe cases from 2016, 2017 ACS universe
- Fit model on 2016 data
- Score model on 2017 data
- Sort predicted vacant probabilities from greatest to least
- Iterate over top percentages by picking a threshold. (i.e. top 10% or 5% of predicted vacant probabilities)
- See how many of those were vacant in 2017 (About 25% of universe is vacant)



# Simulation Results – Predictions

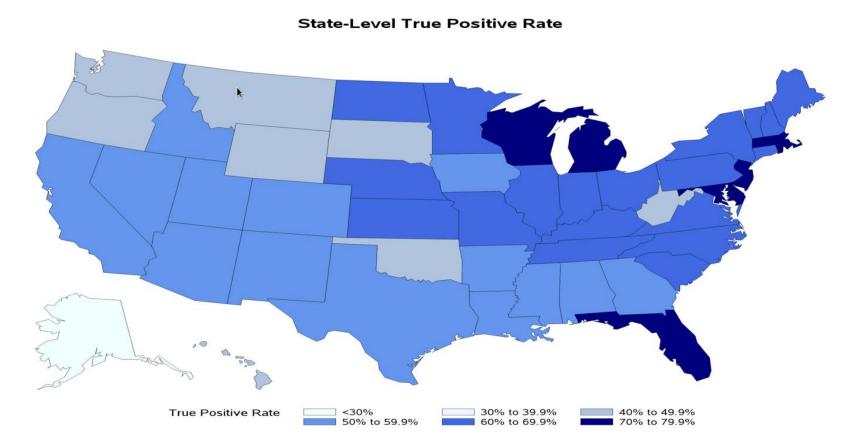
- 1) Can we design a model to reasonably predict vacant cases?
- 2) What threshold should be used to perform treatment?





# Simulation Results – State-Level Predictions

• For Top 10% of vacant predicted probabilities, what is the rate at which the vacancy prediction is correct?



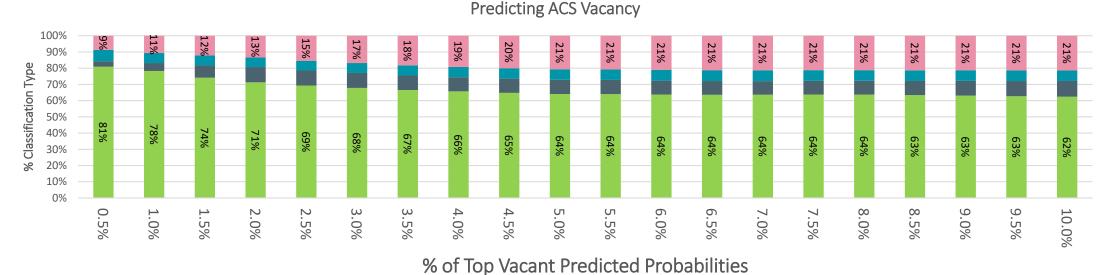


# Simulation Results – Status

- Look at distribution of outcome
- Example: Top 5.0% of vacant predicted probability among mailable CAPI cases:

■ Vacant ■ Not a HU ■ Other

64% vacant, 21% occupied



Occupied



# Simulation Results – State-Level Treatment

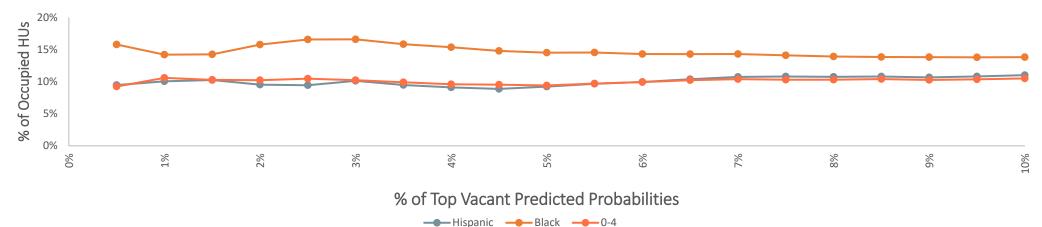
- The universe of mailable CAPI cases has a particular state-level distribution.
- Depending on cost-benefit, we pick a threshold of predicted vacant probabilities to treat.
- Regardless of the top threshold selected, that state-level distribution of the top threshold will not be the same.



# Simulation Results – People in HUs

- Among occupied mailable CAPI cases:
  - 25% have someone who is Hispanic
  - 21% have someone who is Black
  - 15% have someone who is age 0-4
- For the top vacant predicted probabilities, we identify occupied units that have proportionally fewer Hispanic, Black, 0-4 persons

% of Occupied Units With Person of Characteristic...





# **Analysis of False Positives**

- Study top vacant predicted probabilities with non-vacant outcome
- Develop understanding where we might be more sensitive to calling it vacant
  - Use decision tree to create business rules
  - Develop rules where non-vacant outcomes occur in greatest amount

### Example Rule

- Take top 10% of predicted cases
- No Land Use Indicated on Administrative Records
- Not on Delivery Sequence File of previous fall
  - 15% of universe
  - 52% were not vacant



# Conclusions

- Modeling vacant units in the ACS universe can be completed using a combination of address-level, ACS operational, geographic, and administrative records information.
- Cost-benefit analysis will help determine the threshold for using the best predictions.
  - Generally, cases within the chosen thresholds contain relatively fewer members of the hard-to-count groups.
- We observe differential true positive rates across states.
  - We develop business rules to identify false positive cases.
  - Not all false positive cases are occupied units some are addresses without housing units.



# Discussion and Future Work

- Universe does not have to be mailable CAPI cases can include all CAPI cases
- We can use ACS Contact History to update model.
  - Example feed results from first contact into model, update probabilities with that information
- We can use predicted probabilities to alter contact strategy.
  - This is how the information is being applied for the 2020 Census.
- We can use predicted probabilities to change sampling rates.
  - Risk: Changing sampling rate for high probability vacant cases that are occupied inflates variances



# Analyzing Differences between Survey Responses and Administrative Data for Property Value

R. Chase Sawyer American Community Survey Office



# Housing Administrative Record Simulation

- Research goals
  - Simulate use of administrative records (ARs) in ACS
  - Study impact on data products
  - Test feasibility of implementing methods
  - Learn effects on production process

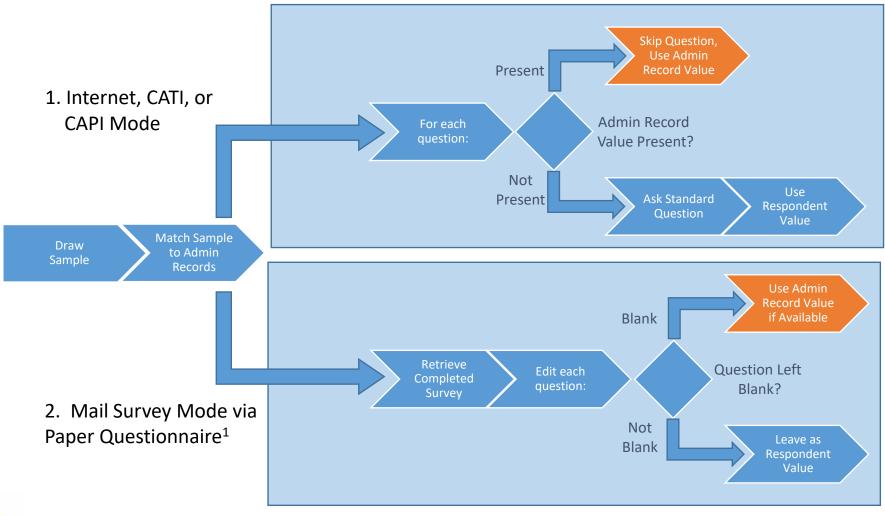


# Simulating this Design

- Used 2015 ACS Responses
- Direct substitution for the four most promising housing items:
  - Year built
     Acreage
     Real estate taxes
     Property value
     Modeled admin data from CoreLogic's Automated Valuation Model (AVM)
- Produced "Simulated" version to compare to "Published" 2015 ACS



# Adaptive Design





1. It would not be feasible to have multiple versions of the mail form so we assume we would ask these questions of all mail respondents.

# Limitations

- Simulated estimates, not a direct comparison
- Results may be confounded by linkage



# Key Measures – Property Value

Key Measure	Published	Simulated	Percent Difference	MOE
Median property value	\$194,500	\$182,300	-6.3	0.1
Property value less than \$10,000	1,045,716	875,020	-16.3	0.6
Property value \$2,000,000 or more	555,865	407,895	-26.6	1.0

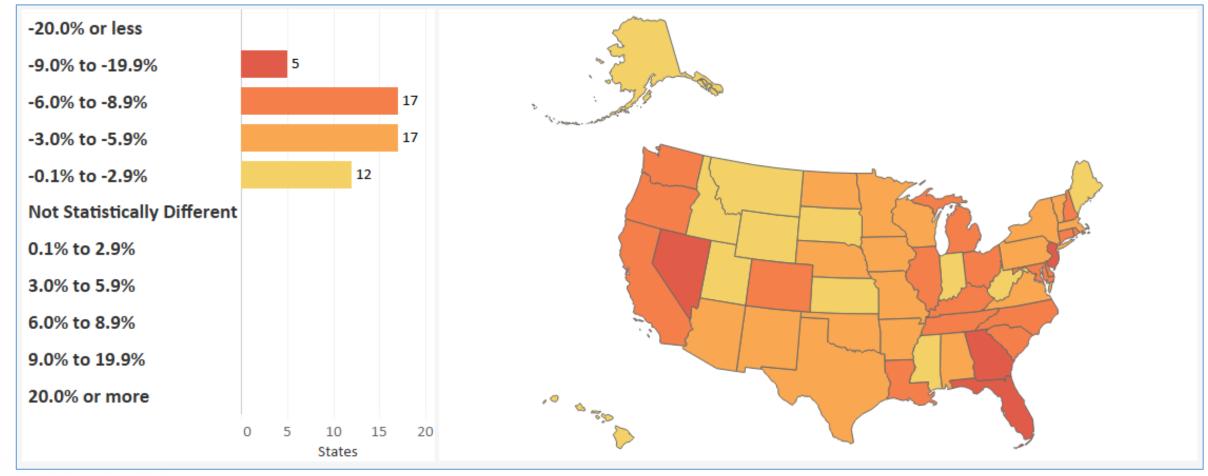


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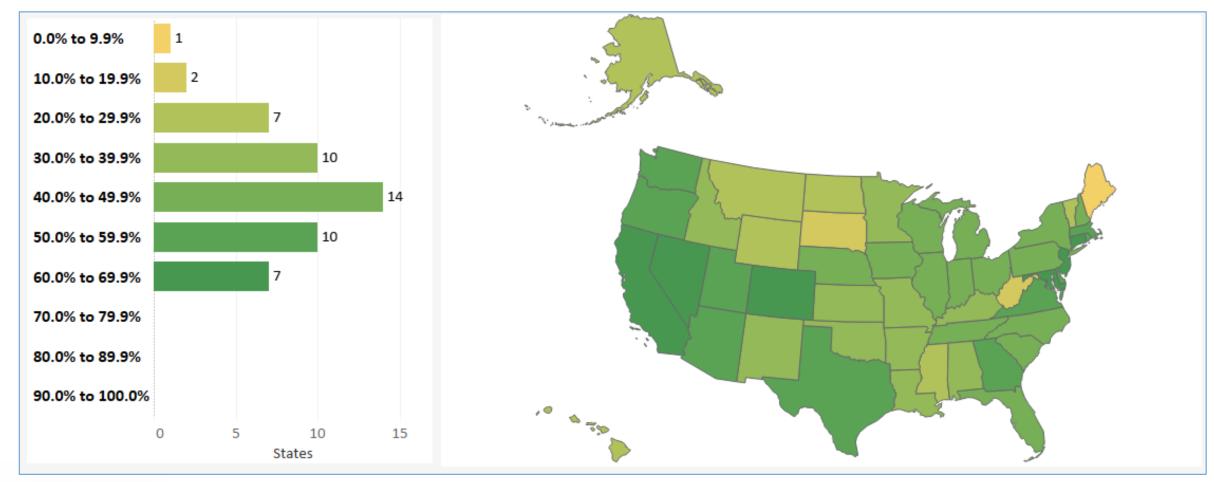


# Percent Difference in Median Property Value: Simulated minus Published - State





#### Burden Reduction for Property Value Question - State



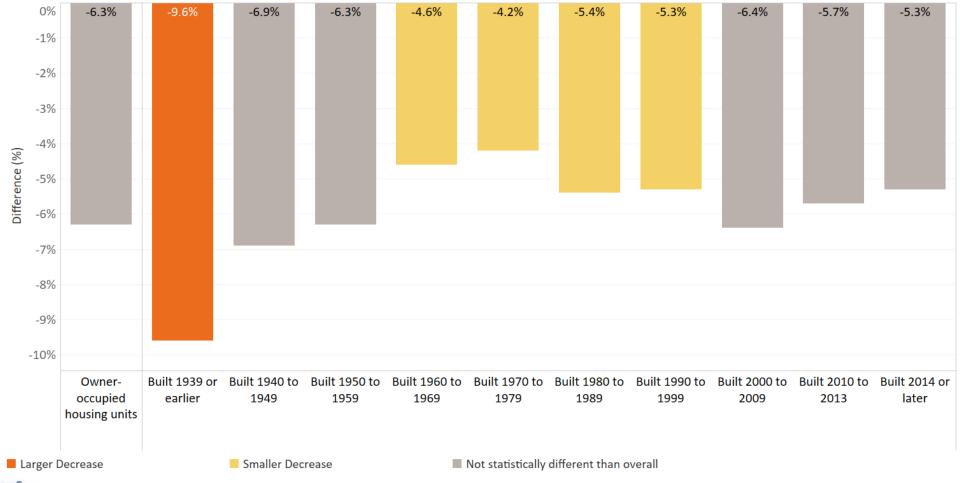


#### Additional data breakouts

- Median property value
  - By year built
  - By year moved in
  - By mortgage status
- Distribution of property value
  - Overall
  - By household income

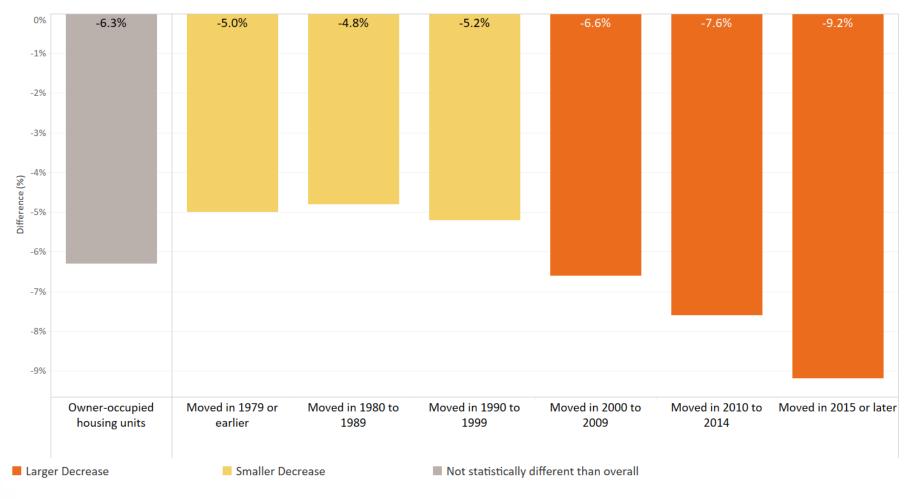


#### Differences in Median Property Value by Year Built



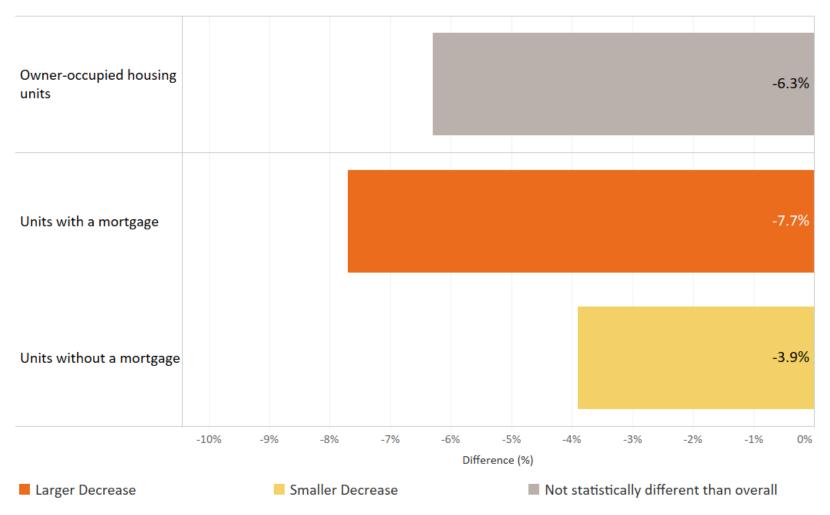


#### Differences in Median Property Value by Year Moved In





#### Differences in Median Value by Mortgage Status





#### Takeaways – Differences in Median Property Value

- Year built
  - No discernable pattern, units built before 1940 have largest decrease
- Year moved in
  - Units that have been moved into more recently have largest decrease
- Mortgage status
  - Decrease largest for units that have a mortgage

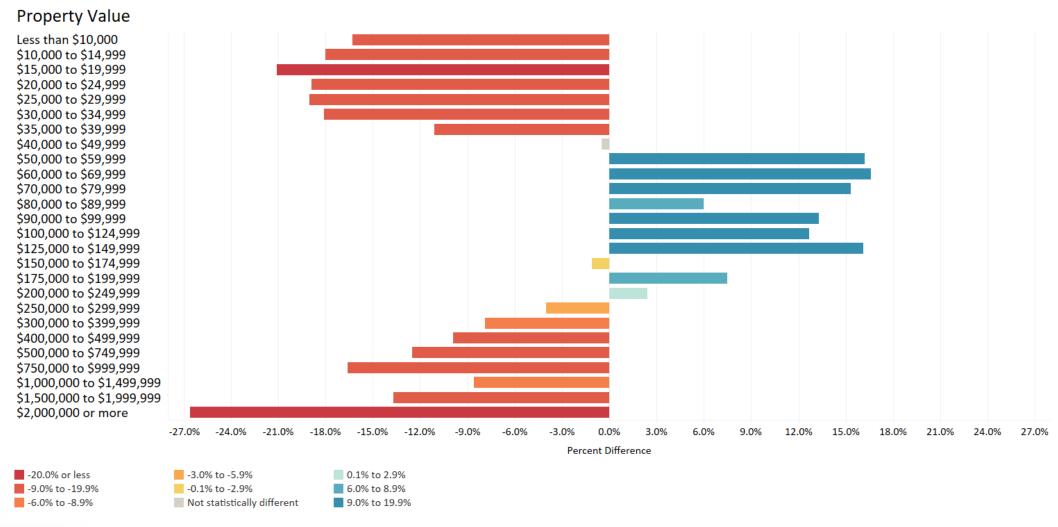


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#### Difference in the Number of Households – Property Value



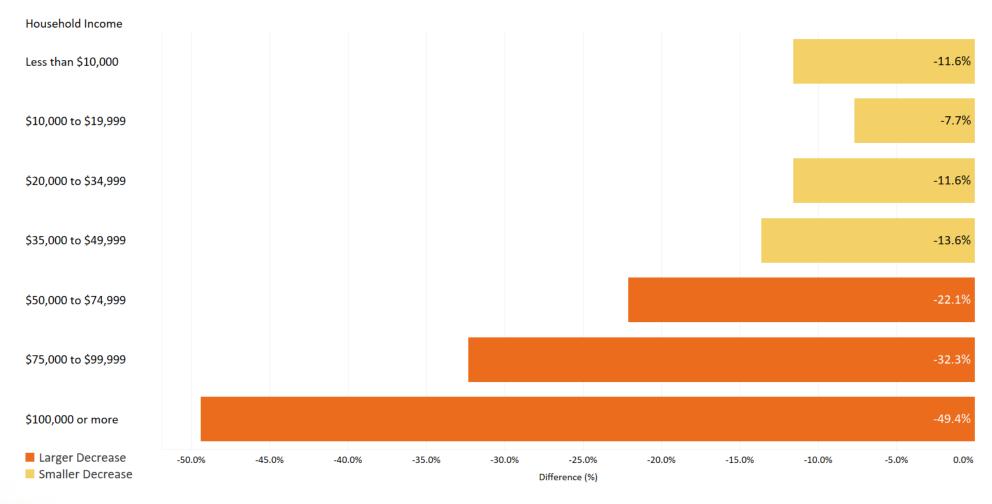


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# Difference in the Number of Households with a Property Value of Less than \$10,000 by household income



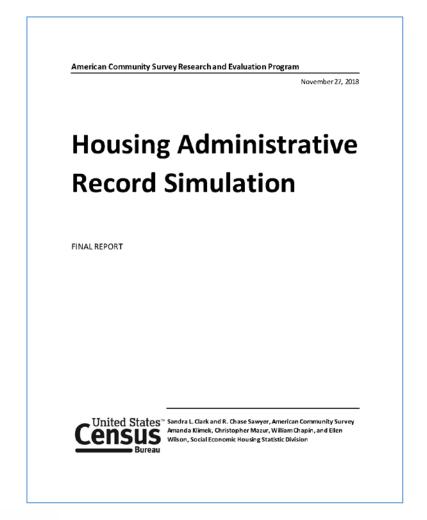


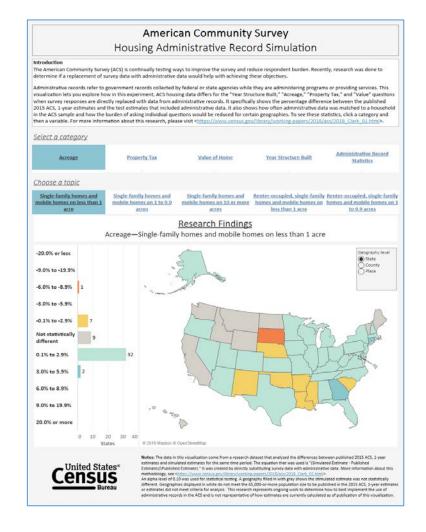
#### Next steps

- Compare ACS responses to new administrative record data
- Look specific at housing characteristics discussed today
- Possible modeling projects



#### Research Products







# Using Alternative Data Sources to Fill-in Missing Values for Demographic Characteristics in the ACS

Sandra L. Clark American Community Survey Office



#### Why and How to Use Administrative Data?



Increase data quality by filling in missing responses and using administrative data to evaluate and enrich survey data



Save time and improve respondent experience by reducing the number of questions asked on the ACS



Provide cost savings by identifying vacant housing units and reducing the need for follow-up visits



Mandated by Title 13 of the U.S. Code to use already available information



#### Background

- AR more accurate than statistical approaches such as hotdeck imputation
- Research for 2020 Decennial Census
  - Hispanic Origin, Race, Age
  - High match rates between 2010 Census reported and AR 90% or better
  - Differences in imputed 2010 Census and AR
    - Increase in Hispanic and race categories when replacing imputed cases
    - Census Imputes more older ages than younger when compared to AR
- Using AR for imputation relatively easy to implement

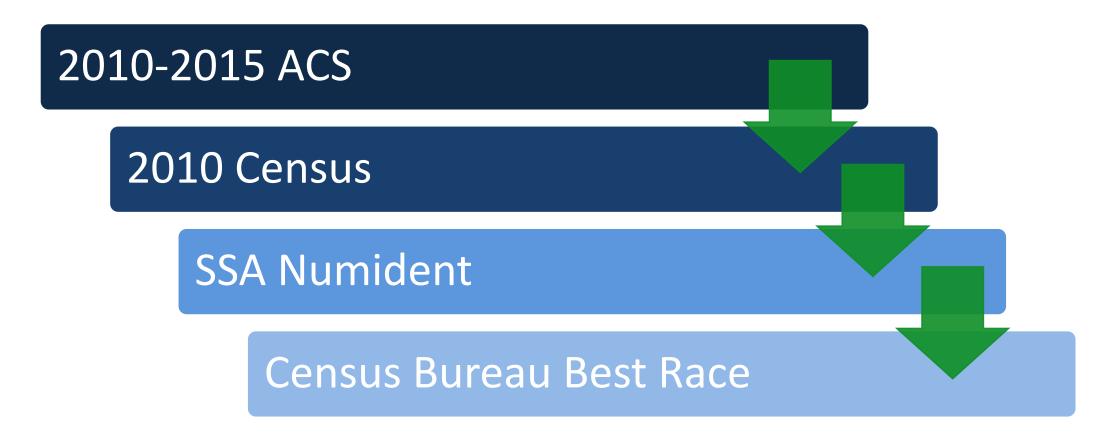


# Case Study: Integrating AR in the ACS Edit and Imputation Procedures

- Uses 2016 ACS response data
- Test items: Age, Sex, Race, Hispanic Origin, Place of Birth
- Incorporates survey, census, and AR data in lieu of imputation
- Simulated data will be run through ACS edits to create estimates to compare with published 2016 ACS estimates
- Preliminary research:
  - Does not include full edit run
  - Cannot determine full impact of edit run on other survey items or clean-up of AR data
  - Replaces missing with AR
  - Uses that file to determine preliminary estimates

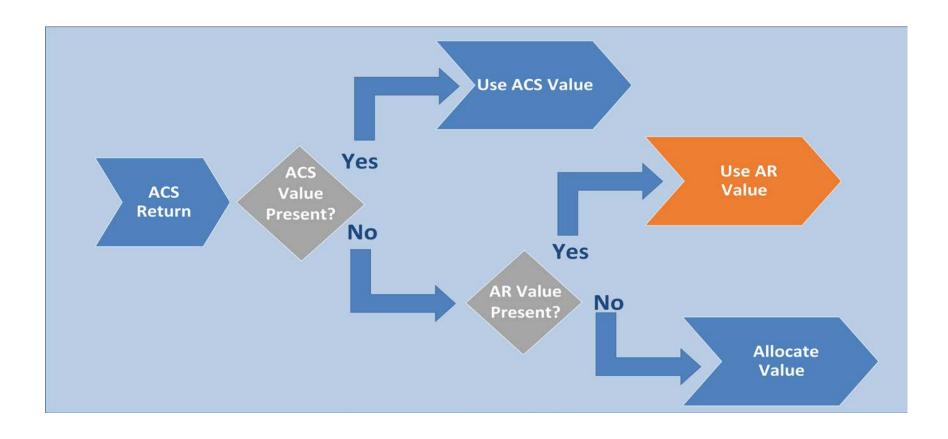


#### Hierarchy of AR Sources





# Integrating AR in the ACS Edit and Imputation Procedures – Adaptive Design





#### Research Questions

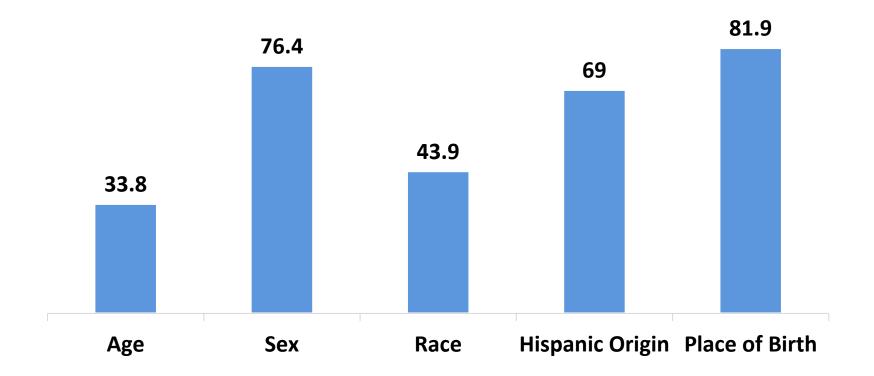
- 1. What proportion of ACS respondents do not provide a response?
- 2. What percent of missing values can be filled-in with available AR data?
- 3. What proportion of the AR values match the ACS allocated values?
- 4. Does using AR change the distribution of the tested items when compared to published estimates?
- 5. Is there any effect on other survey items, besides those included in the test?



- 1. What proportion of ACS respondents do not provide a response?
  - Age **1.0**%
  - Sex 0.4%
  - Race 1.6%
  - Hispanic Origin 1.6%
  - Place of Birth 6.8%

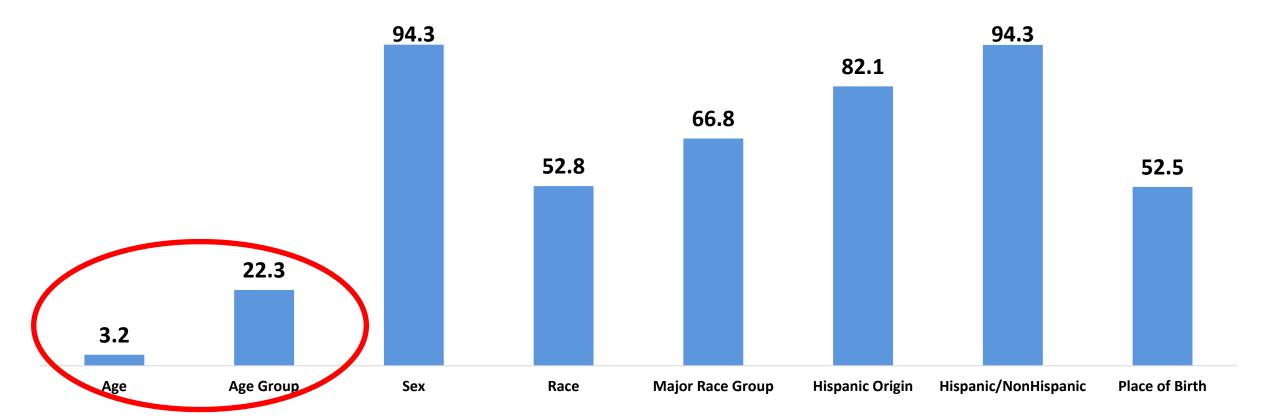


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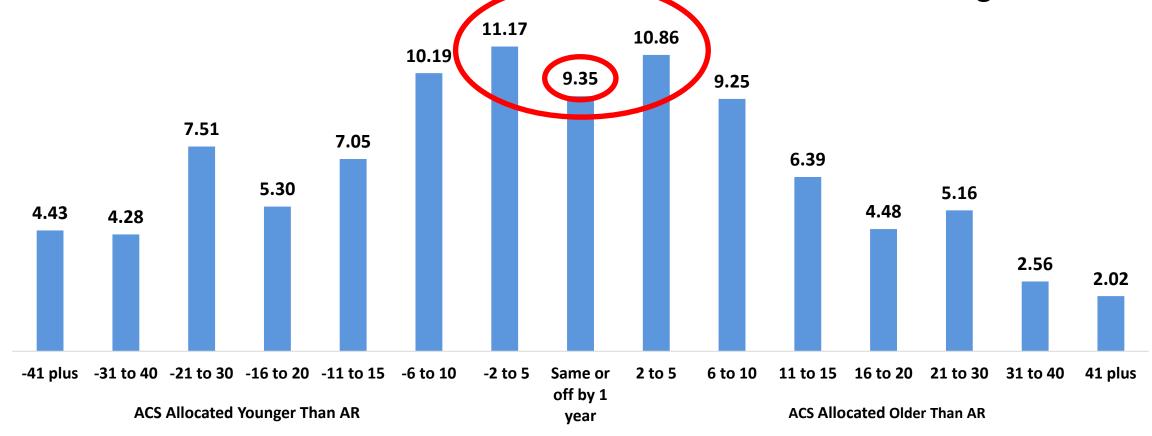


3. What proportion of the AR values match the ACS allocated values?





Percent Differences in ACS Allocated Value and AR Value for Age





#### Preliminary Conclusions

- AR is available to fill-in a large percent of missing ACS values
- Fairly low match rates suggests ACS edits may not accurately capture missing response
- Using AR in lieu of statistical approaches may improve data quality



#### Next Steps

- Study the differences between AR values and ACS allocated values
- Run the test dataset with AR through ACS edits and compare resulting item distributions with published distributions
- Determine if using AR to fill-in for missing values impacts other items not included in the test
- Develop method to quickly apply edits to test additional items for AR allocation
  - Using AR to allocate values for other items with higher missing data rates will provide larger benefit to ACS program



# Using Administrative Data in ACS Production – Tentative Target Dates

	2016-2020	2021	2022	2023	2025	2030
Evaluating Administrative Sources						
Demographic Items		Age, Sex, Race, Hispanic Origin				
Housing Itoms			Acroago	Year Built, Property Taxes,		
Housing Items			Acreage	Property Value	Question Changes	
Income Items					Reference Period	Applicable Income Items



# Linking ACS and IRS Data to Assess Educational Attainment by Family Income

Leah Clark
Center for Economic Studies



### Tracking educational attainment by childhood family income

- Cross-sectional surveys like the American Community Survey (ACS) offer measures of educational attainment on a national scale
  - Pros: Large sample size, collected annually
  - Con: Lacks reliable information about childhood family income
- Studying this topic with other data sources brings up other challenges
  - Longitudinal surveys have information about childhood family income but smaller sample size and fewer cohorts
    - For example, Bailey & Dynarski (2011) use National Longitudinal Surveys of Youth data to assess college attendance and completion, but are limited to two cohorts
  - Administrative records offer annual population-level statistics, but are limited in scope
    - For example, Chetty et al. (2014) use tax records to study college attendance, but cannot assess college completion



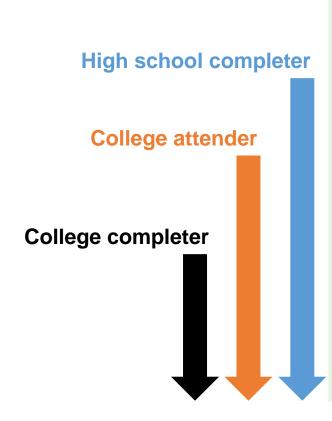
#### Our contribution

- We link ACS data to Internal Revenue Service (IRS) form 1040 data to bring a measure of childhood family income into the ACS
  - Making a cross-sectional survey longitudinal by leveraging administrative data (Dynarski 2014)
- We produce reliable, annual statistics on high school completion, college attendance, and college completion by childhood family income
  - Cohorts born from 1983-1991
  - Paired with detailed demographic and geographic characteristics, this represents a major step forward for measuring inequality in educational attainment



#### Defining educational outcomes

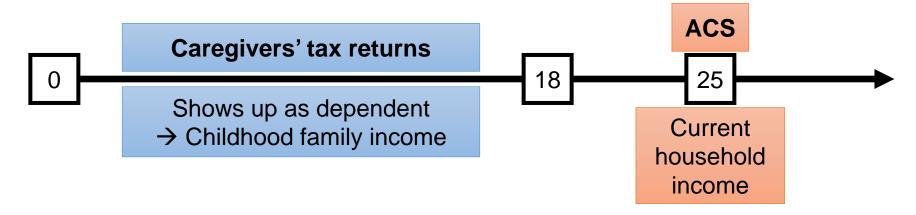
- Derived from ACS question concerning *highest* level of educational attainment
- High school completion includes regular high school diploma, GED/alternative credential attainment or higher
- College attendance includes "some college credit" or higher
- College completion is defined as a bachelor's degree or higher
  - Measures that include associate's degrees are also an option





)	this If cu	What is the highest degree or level of school this person has COMPLETED? Mark (X) ONE box. If currently enrolled, mark the previous grade or highest degree received.				
	NO S	SCHOOLING COMPLETED				
		No schooling completed				
	NURSERY OR PRESCHOOL THROUGH GRADE 12					
		Nursery school				
		Kindergarten				
		Grade 1 through 11 – Specify grade 1 – 11 →				
		12th grade – NO DIPLOMA				
	HIGH	SCHOOL GRADUATE				
		Regular high school diploma				
		GED or alternative credential				
	COL	LEGE OR SOME COLLEGE				
		Some college credit, but less than 1 year of college credit				
		1 or more years of college credit, no degree				
		Associate's degree (for example: AA, AS)				
		Bachelor's degree (for example: BA, BS)				
	AFTI	ER BACHELOR'S DEGREE				
		Master's degree (for example: MA, MS, MEng, MEd, MSW, MBA)				
		Professional degree beyond a bachelor's degre (for example: MD, DDS, DVM, LLB, JD)				
		Doctorate degree (for example: PhD, EdD)				

#### Defining childhood family income



- 1. Locate ACS respondents as dependents in IRS form 1040 data
- 2. Pull household adjusted gross income during the years they turned 15, 16, or 17, and adjust for inflation
- Define childhood family income as the average of those three years, ignoring missing or negative values
- 4. Rank respondents by childhood family income within each birth cohort and split into three equal-sized groups (high, middle, low)



#### New linked dataset

### ACS 2006-2017



#### Administrative Records



### Over 1 million linked respondents

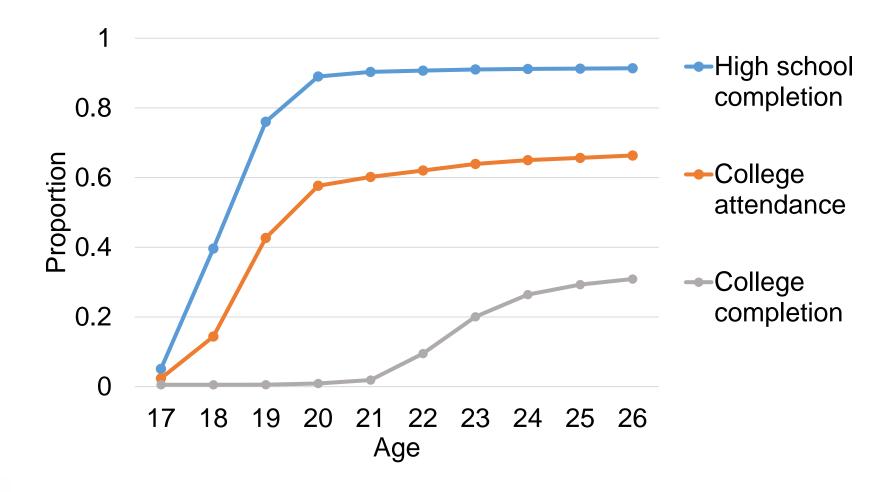
- Respondents born 1983-1991
  - Surveyed at ages24-26
- Variables:
  - Educational attainment
  - Race/ethnicity
  - o Sex
- Excludes noncitizens

- IRS form 1040
  - 0 1998-2014
  - Variable: Childhood family income
- Census Numident
  - Social Security
     Administration
     records
  - Variable: Date of birth

- Childhood family income measures for 87% of the population
- Sample weights
   rescaled by inverse
   probability of having a
   measure of childhood
   family income

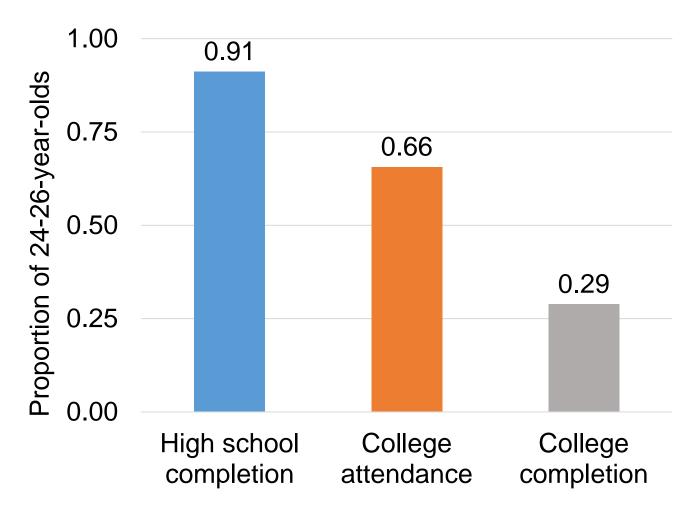


#### Educational attainment by age





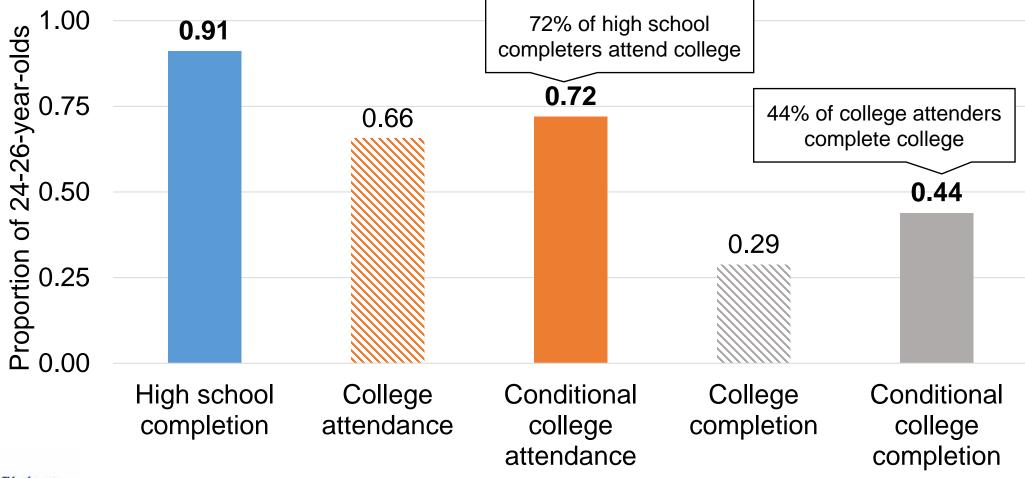
### What is the educational attainment of young people born between 1983 and 1991?





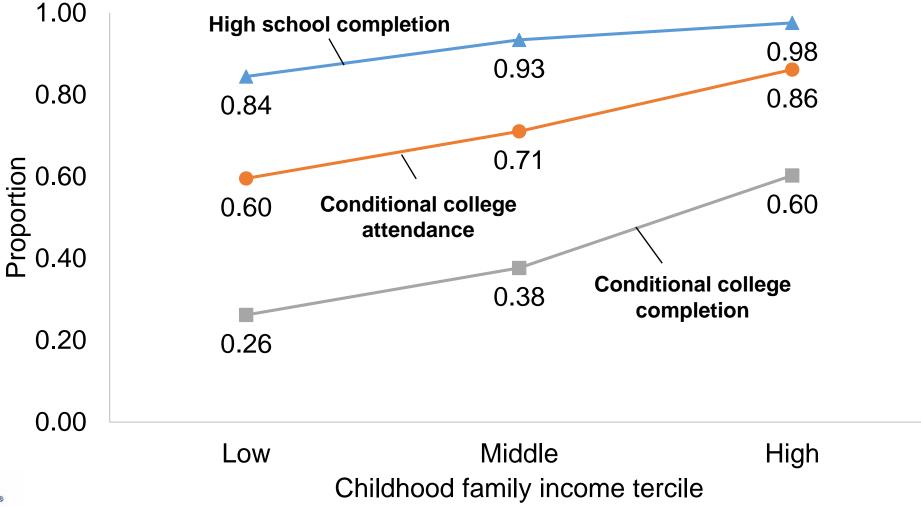
Source: ACS 2006-2017, Census Numident and IRS 1040s 1998-2014

## Conditional rates allow us to isolate the inequality that arises at each education level





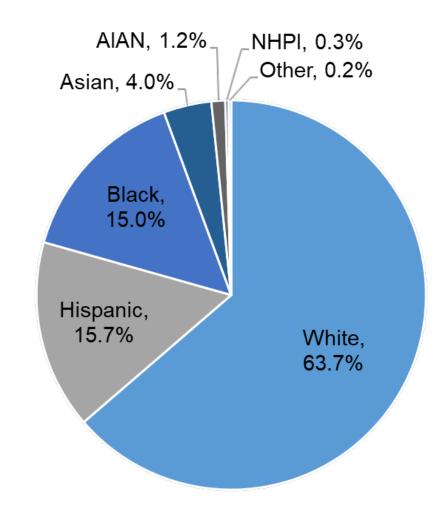
## How does educational attainment vary by family income?





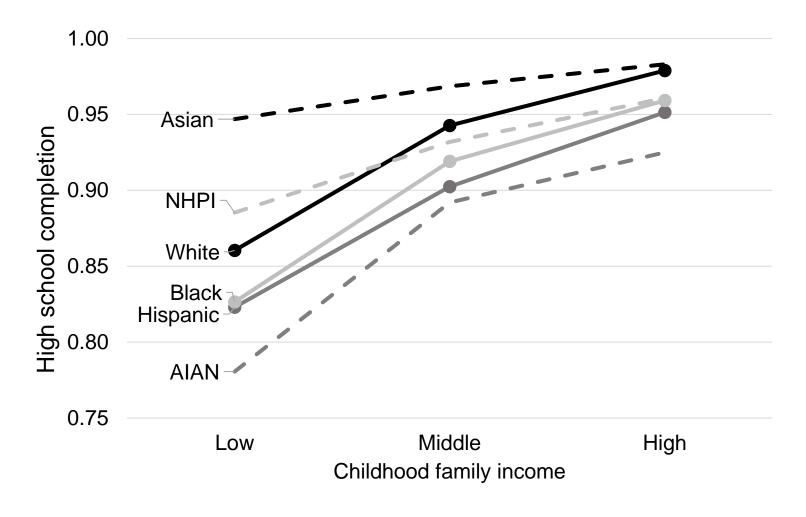
# Race/ethnicity

- We use the following race/ethnicity categories:
  - Hispanic (of any race), and
  - Non-Hispanic:
    - White
    - Black
    - Asian
    - American Indian/Alaskan Native (AIAN)
    - Native Hawaiian/Pacific Islander (NHPI)
    - Other



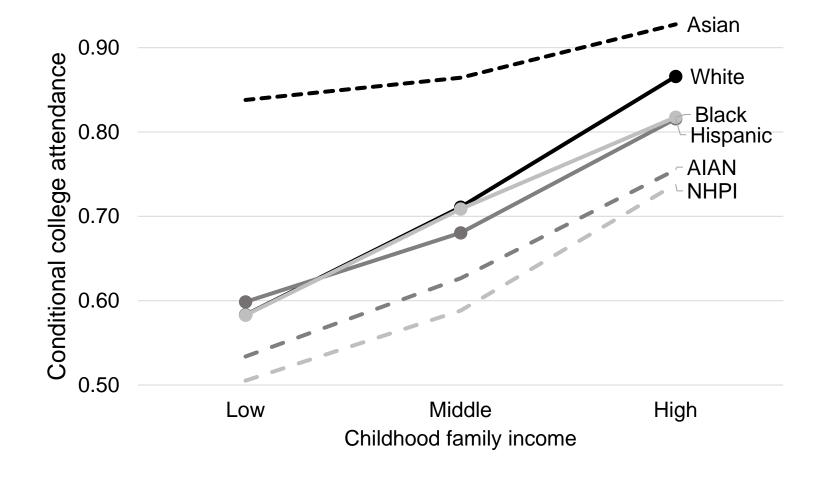


# High school completion by income & race



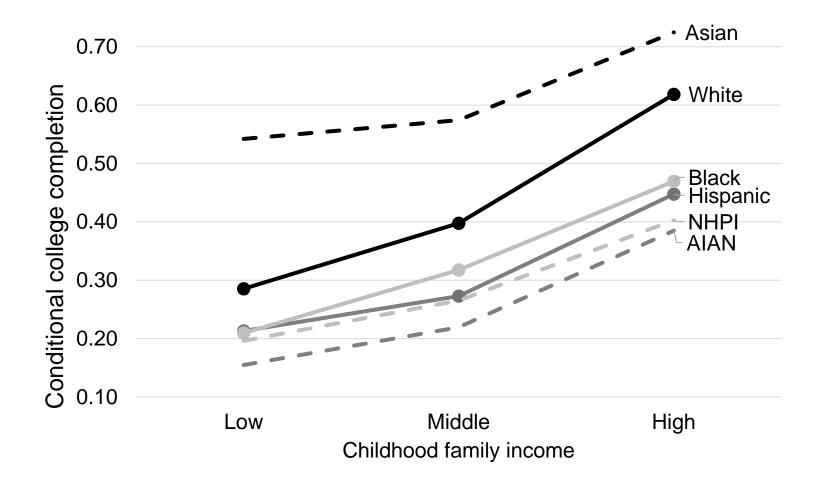


## Conditional college attendance by income & race





# Conditional college completion by income & race



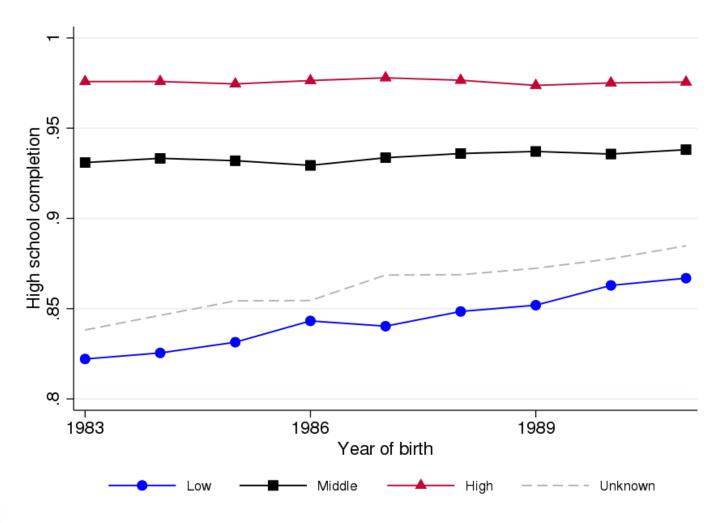


### Trends in educational attainment

- Rather than pool over birth years, we can plot attainment for each year and income group
- We use regressions to test changes in income gaps
  - Can also test changes by income and race



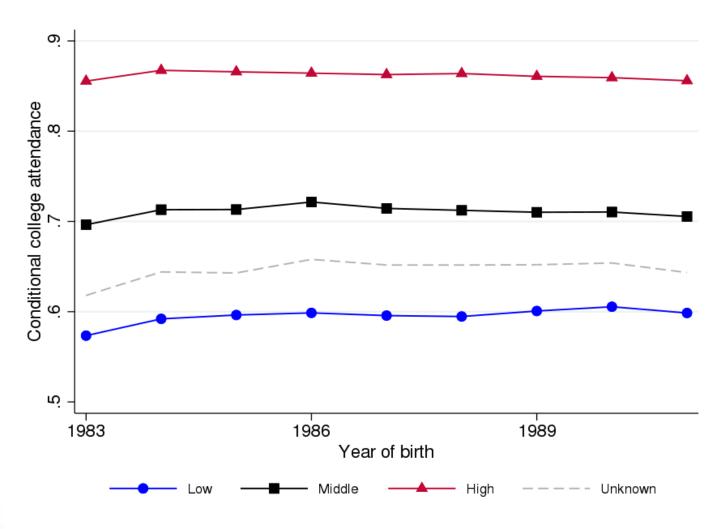
### Low-income young people made gains in high school completion



- High school completion rate for low-income young people grew by 4 percentage points
- The income gap in high school completion narrowed by more than one-fourth



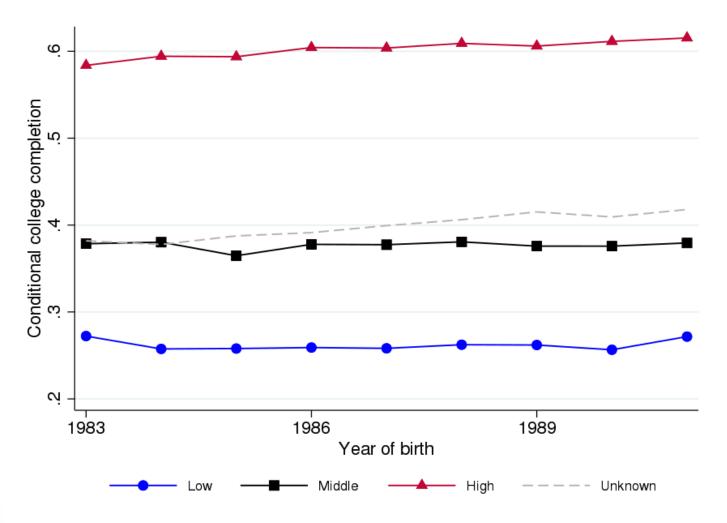
### Small low-income gains in college attendance



- Low-income high school completers made very modest gains in college attendance
- The income gap narrowed by less than one-tenth



### The income gap widened in college completion



- High-income college attenders became more likely to complete college
- The income gap continued to grow



## Trends expand on existing literature

- High school graduation rate stagnant for young people born before 1980, but rising for cohorts born in the 1980s, especially for Black and Hispanic young people (Heckman & LaFontaine 2010; Murnane 2013)
  - We document that rise is driven by low-income young people
  - Low-income Black and Hispanic respondents make large gains, but low-income AIAN respondents do not make gains
- The income gap in college attendance rose for cohorts born 1961-1982 (Bailey & Dynarski 2011)
  - Like Chetty et al. (2014), we find a slight decline for cohorts born in the 1980s
- Bailey & Dynarski also find growth in the income gap in college completion
  - We show that the gap has continued to grow



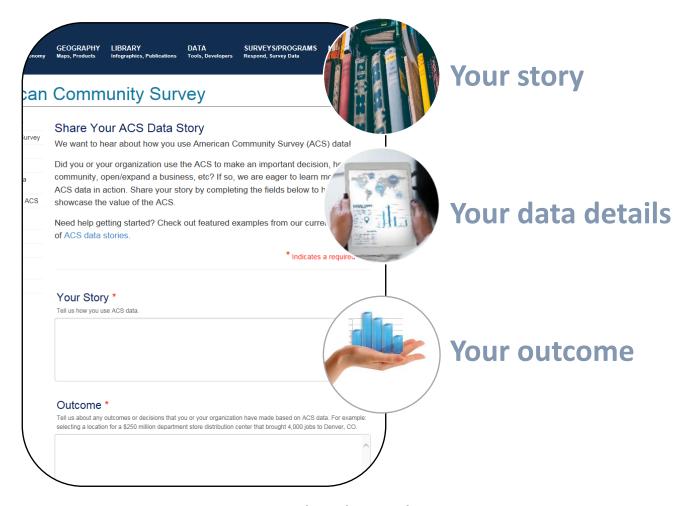
### Conclusion

- Linking measures from administrative data to cross-sectional surveys opens many new analysis opportunities
  - Cross-generational income measure
- Large and persistent disparities in educational attainment by childhood family income
  - Low-income gains in high school completion
- Income gaps vary across racial subgroups, but they are consistently large within subgroups
- Rates of educational attainment differ by racial subgroups, and so do trends
  - American Indian and Alaskan Native young people experience low levels of educational attainment, and are not showing signs of convergence with other subgroups



### The American Community Survey

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Source Us:

U.S. Census Bureau's [YYYY – YYYY] American Community Survey [1/3/5]-year [estimates/statistics/data release]



## For More Information

#### Realizing the Promise of Administrative Data for Enhancing the American Community Survey

https://www.census.gov/programs-surveys/acs/operations-and-administration/agility-in-action/administrative-records-in-the-american-community-survey.html

#### **Housing Administrative Record Simulation**

https://www.census.gov/library/working-papers/2018/acs/2018 Clark 01.html

#### **Housing Administrative Record Simulation Data Visualization**

https://www.census.gov/library/visualizations/interactive/housing-admin-record-simulation.htm

#### **Reports Evaluating Administrative Data Sources**

https://www.census.gov/content/census/en/programs-surveys/acs/library/publications-and-working-papers/research-and-evaluation.All.html/

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